7. Data Analysis and Reporting

Data analysis and reporting are essential components to monitoring long-term ecosystem health, due to the importance of communicating important information to various constituents. Reporting and analysis are directly connected to the overall goals for the program, presented in Chapter 1. To be successful in communicating the value of monitoring, however, it is essential to identify goals of reporting and appropriate audiences for each reporting type. Following are a list of objectives for analysis and reporting that the GRYN would like to accomplish:

- To ensure scientific defensibility of the results of monitoring, which we will achieve by including parameter estimates, test results and model selection
- To aid in interpretation of results for various constituents (i.e., general public, park managers, etc.)
- To synthesize the strengths and weaknesses of the monitoring effort in meeting National I&M program goals
- To provide a measure of the state of the parks to various constituents (i.e., park managers, general public, etc.)
- To identify possible warning signals of abnormal conditions and bring this information to the attention of managers and the public
- To provide information from monitoring that will help to assess the performance of the I&M program and the parks with respect to legal mandates (i.e., GPRA), and to report such information in a usable format for park staff

The way in which the analytical methods the GRYN uses will help the network reach the overall I&M goals listed in Chapter 1 are shown in Figure 7.1. In the subsequent sections, the methods the GRYN will use to analyze and report on monitoring are outlined.

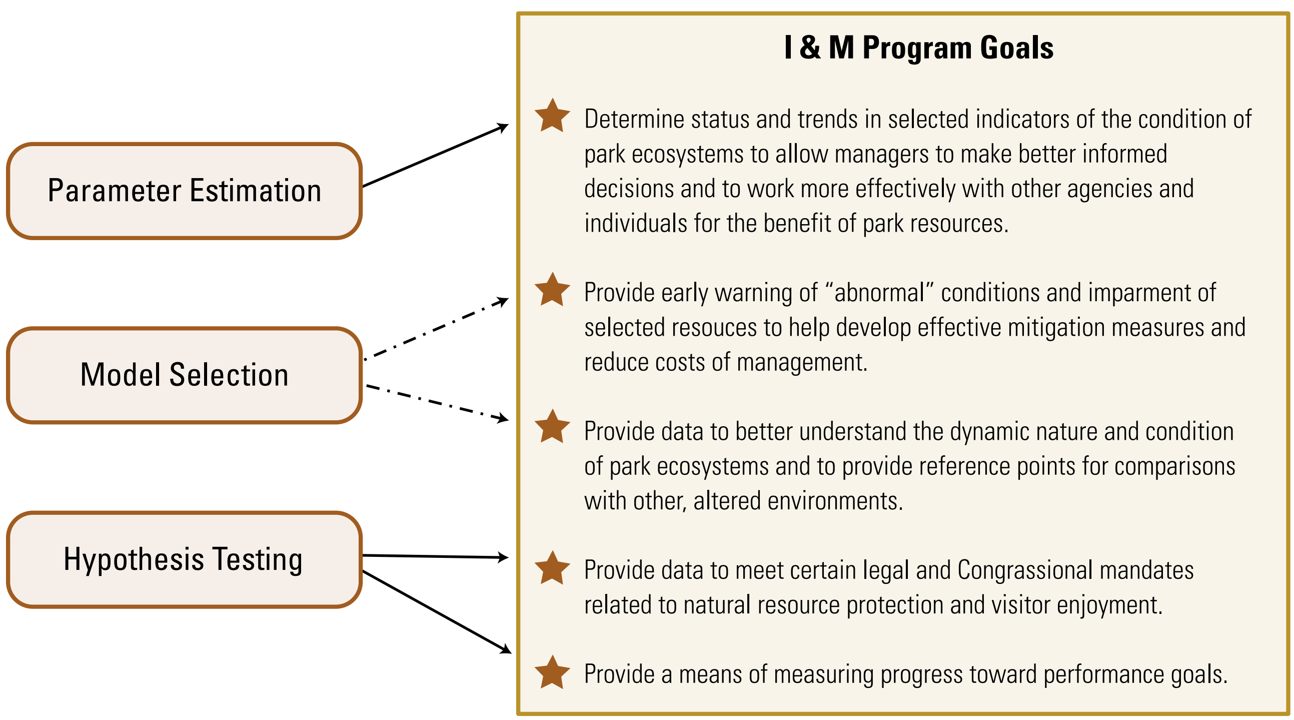

FIGURE 7.1 Conceptual relationship between major types of analysis and the primary, but not exclusive, I&M goals that they will facilitate achieving.

DATA ANALYSIS

One of the guiding principles in the National Park Service FY2001-2005 Strategic Plan (NPS 2001b) is "applying scientific information to park management decisions to preserve park resources." This goal was also outlined in the Natural Resource Challenge (NPS 1999) and the development of the I&M program (NPS 2004a). Using the sampling designs described in Chapter 4 will ensure that the data collected meets the highest standards of scientific quality. Then, through analyses and interpretation, the GRYN will communicate valid inferences about the resources being monitored. The following sections outline the guiding principles used to determine the appropriate analysis in a given context. Due to the detailed nature of analysis techniques, the specific analyses used for each vital sign will be found in the monitoring protocol; this chapter serves as a conceptual overview of the analytical methods the GRYN plans to use.

Parameter Estimation

Although there are many ways of categorizing analyses, three primary types of analyses are considered here (parameter estimation, hypothesis testing and model selection). While these broad categories are not entirely mutually exclusive, parameter estimation is primarily concerned with measuring and describing the attributes of a population in terms of its distribution and structural features. Because one of the primary goals of the I&M program is to determine the status and trends of selected vital signs, the appropriate category of analyses will be most likely in the form of parameter estimation: either estimation of the state of a given resource (status) or the change in that resource state over time (trend). Therefore, parameter estimation will certainly be one, if not the, most common type of analysis in our program. Using this method will require an understanding of the structural features of the distribution from which the sample is drawn, including estimates of central tendency and variability. Some of the properties that we will be concerned about in our estimation of parameters are bias, precision and confidence; each is discussed below.

1. BIAS, PRECISION AND CONFIDENCE

With respect to parameter estimation, bias represents the tendency for a parameter estimate to systematically differ from the true value. In other words, if the expected value of the estimate (e.g., the average from repeated samples) is equal to the true value of the parameter, then the estimator is considered unbiased. This differs from precision, which represents how much variation there is in the estimates (Figure 7.2). The GRYN will attempt to ensure unbiased estimates by using a sound sampling design and unbiased estimators (e.g., based on maximum likelihood), and staff will ensure the most precise possible estimates by considering the sample sizes required for estimates of a given precision (see Chapter 4).

Precision can reflect variation in the data (i.e., the standard deviation) or confidence in the estimates (i.e., the standard error). Because the estimate of the population parameter is based on random sampling, the estimates themselves can be considered a random variable (Williams et al. 2001). Consequently, it is necessary to recognize an important distinction between these components of precision. Variation in the data is estimated by the standard deviation (SD) and is not a function of sample size. In contrast, variation in the estimates must take into account the variation in the data, in addition to how well the population was sampled (i.e., sample size), and is measured by the standard error (SE). Thus, the SD will be reported where appropriate to illustrate variation in the data; however,

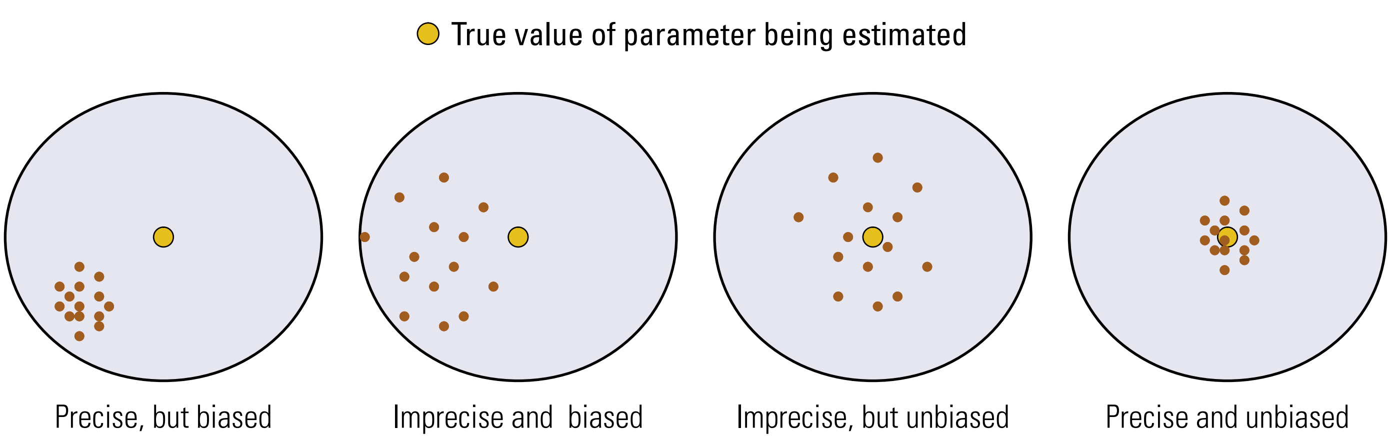

FIGURE 7.2 Conceptual diagram illustrating the difference between bias and precision for a given parameter estimate.

for most parameter estimates, the primary concern will be the level of confidence in the estimates, and therefore the SE and confidence intervals will always be reported.

Hypothesis Testing

The second general category of analysis is hypothesis testing and most likely will be more limited within the network protocols. This method of analysis will be used when the state (status) of a given resource is tested against a specified reference such as a legal threshold or desired condition. In the context of I&M program goals, this would likely be for testing whether or not certain legal or congressional mandates have been met or whether or not performance targets have been achieved. Thus, the GRYN does not plan to test scientific hypotheses, which might be better suited to a research program using an experimental approach; rather, the GRYN will use this approach to test whether or not the uncertainty about the parameter estimates warrants conclusions about the relationship between a given resource state and the reference to which it is being compared. This method is considered as a type of statistical hypothesis testing primarily because it will be extended to included comparisons with a priori reference values. However, the focus of the network will be on estimating parameters to ensure that biological and statistical significance are appropriately distinguished, following Yoccoz (1991).

Model Selection

The third general class of analyses that the GRYN will use is model selection, which helps to better understand the dynamic nature and condition of park resources. To understand these dynamics, it is necessary to advance beyond the estimation of parameters (although it is likely that parameter estimation will be included in the context of specified models) to include the relationships among resources, ecosystem drivers and stressors. A model-selection approach considers the evidence within the data in support of a suite of candidate models that represent multiple hypotheses, in contrast to a hypothesis testing framework, which seeks to determine "the" correct alternative hypothesis.

1. PRINCIPLE OF PARSIMONY

Our model selection is based on the principle of parsimony: the notion that an appropriate model should contain just enough parameters to adequately account for the variation in the data, since adding and deleting parameters has important consequences (Burnham and Anderson 2002). Under fitting (i.e., having too few parameters) can result in a model that does not adequately represent the information contained within the data. In contrast, over fitting (i.e., having too many parameters) may improve the fit of the model to the data at a cost of reducing the precision of the parameter estimates, sometimes to the point of them being of little value. Thus, the principle of parsimony leads to finding the right balance between under and over fitting the model. This balance can be expressed in terms of a tradeoff between bias (i.e., systematic lack of fit) and precision (i.e., the confidence of our parameter estimates) (Figure 7.3). The addition of parameters in a model reduces bias but also decreases precision. Likewise, reducing the number of parameters increases the precision of parameter estimation, but also increases bias. Model selection does not seek to find the "true" model (Burnham and Anderson 2002); rather, it seeks to find the best approximation of the information contained within the data by summarizing the major systematic effects together with the nature and magnitude of the unexplained (random) variation (McCullagh and Nelder 1989). Because, as Box (1979) once said, "all models are wrong, but some are useful."

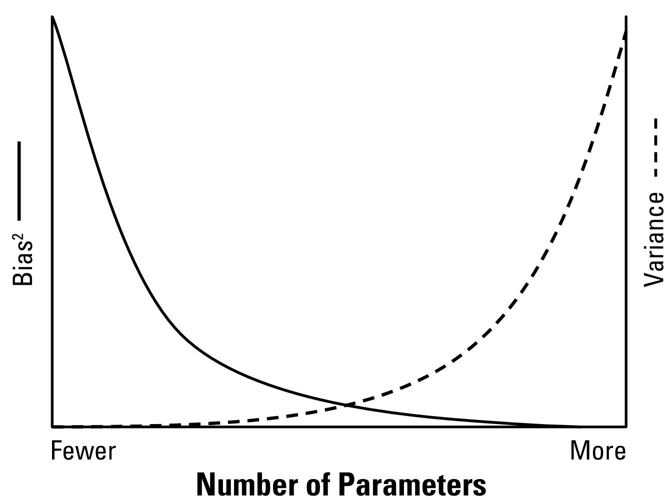

FIGURE 7.3 Conceptual diagram illustrating the tradeoff between bias and precision imposed by the number of parameters included in a given model (adapted from Burnham and Anderson 1992).

2. AN INFORMATION THEORETIC APPROACH

Given that essentially all model-selection approaches embody the principle of parsimony to some extent (Hosmer and Lemeshow 1989, Breiman 1992, Burnham and Anderson 2002), the question arises as to how the network will use this principle. Step-wise procedures, which tend to automate the model selection process by progressively filtering model terms either through the addition (forward selection) or subtraction (backward elimination) of terms in a given model have been widely criticized for producing spurious and inconsistent results (summarized by Hocking 1976, James and McCulloch 1990). In a sense, step-wise approaches to model selection essentially treat each "step" as if it were an independent hypothesis test to be "rejected" or "accepted." Further, step-wise and other mechanical selection processes (e.g., best subsets) have also been widely criticized because they can result in biologically implausible models (Greenland 1989, Hosmer and Lemeshow 1989) that frequently include "noise" variables (i.e., irrelevant) (Flack and Chang 1987). Hocking (1976) concluded that any advantages of step-wise procedures seemed to be outweighed by "all-possible" or optimal algorithms. Clearly, "all-possible" approaches can suffer from the same criticism of including irrelevant variables that are not biologically plausible.

Considerable attention has emerged in recent years regarding the use of information theoretic approaches such as Akaike's Information Criteria (AIC) (Akaike 1973) as a basis for model selection (e.g., Burnham and Anderson 2002). In contrast to treating steps of the model selection process as a series of hypothesis tests, AIC treats the model selection process as a problem in optimization of the balance between model fit and precision (Spendelow et al. 1995). AIC optimizes the fit of a model balanced against the cost of adding excessive parameters. The statistical foundation for this approach has been well described (e.g., Akaike 1973, Anderson et al. 1994, Burnham and Anderson 2002). One variation on this basic form of AIC is when overdispersion (i.e., the sampling variance exceeds the expected value for the model) is present. In such a case, traditional likelihood theory, from which AIC was derived, is not reliable and the variance may need to be generalized by using an estimated inflation factor. In this case, AIC is then modified to an alternative quasi-likelihood QAIC to account for overdispersion. The second variation on the basic form is a correction factor to account for small sample sizes which can be applied to either of the above forms as AICc or QAICc. The modifications for overdispersion and small sample sizes are discussed in detail elsewhere (e.g., Anderson 1994, Burnham and Anderson 2002).

It is recognized that this approach is not a panacea for all cases (i.e., AIC does not work equally well for all model types and situations), although it does embody the principle elements that are sought for model selection. Thus, AIC will be an essential tool for model selection, although in some cases where the situation is not conducive to AIC, the network may depart from this approach. These will be considered on an individual basis as they arise.

3. MODEL AVERAGING

When deriving inference about the dynamics and condition of park resources using model selection, we must recognize that there is uncertainty associated with the model selection itself. Buckland et al. (1997) proposed a procedure to better account for the uncertainty of model selection for deriving parameter estimates based on an average of several plausible models, rather than a single "chosen" one. This approach weights the models according to AIC values; thus the most plausible models receive the highest weight, while the least plausible models receive little or no weight. The GRYN will use model averaging for estimating parameters of interest when the parameters are derived from a selected model where alternative models exist.

Sampling Error vs Process Variation.

One of the key components of the I&M program is assessing how particular vital signs change over time. However, it is important to note that it is seldom possible to estimate parameters without some sampling error. Consequently, when looking at changes over time, it is necessary to consider that, in addition to real environmental variation that occurs over space and time in the population (and is thereby reflected in our measurements), there is also a sampling error associated with the measurement. Distinguishing these real changes in the population from measurement error is sometimes difficult. The traditional "sampling variance" that is estimated from the data typically includes an element of both types of error, which are highly confounded. Burnham et al. (1987) provide a theoretical framework for partitioning the variance into error that is attributable to sampling and parameter (process) variation. Where feasible, the network will use this, or alternative approaches as they are developed, to estimate the true variation in the populations of interest over time.

Frequentist vs Bayesian Statistics

Traditional statistical approaches, often called frequentist (and described in the above sections), are founded in the notion of probability, and rely on data generated from a given study (or studies) to derive inference. These data are typically assumed or fitted by a statistical distribution from which parameters are estimated. Inferences are typically derived from summaries and/or comparisons of the parameters being estimated in the context of hypotheses, the most common of which is the null hypothesis. As such, the inferences derived rely on the dataset(s) being used in the analysis and auxiliary information for the analysis is limited to that which can be coupled with the dataset(s) being analyzed. Thus, one of the criticisms of this approach is that information regarding the states of the system, which are not part of the study being analyzed, are either ignored completely or synthesized in an ad hoc manner to derive inference beyond the particular study.

An alternative approach that has gained increasing recognition is Bayesian statistics, where cumulative information about the parameter(s) of interest is used as a starting point in the form of a prior probability distribution. The analysis for a given dataset then derives a new (updated) distribution called a posterior probability distribution that incorporates the likelihood of the data given the prior beliefs (i.e., prior distribution). Such an approach is intuitively appealing because it takes into account all of the information accumulated on a given problem and enables a more direct assessment and description about the probability of a given hypothesis being true, rather than merely a rejection or acceptance of it being true based on a subjective threshold (i.e., the α-level or p-value of traditional statistics). Some of the drawbacks of this approach include: it is computationally more difficult; and a lack of universal agreement exists among statisticians about the nature and behavior of the distributions (particularly the prior distribution, which may incorporate subjective components as part of a probability distribution). The most logical place where a Bayesian approach seems appropriate for the network is when (if) a model-based approach to inference is undertaken (see Chapter 4). In this context, a Bayesian approach may be well suited to continually updating the beliefs about a particular model (hypotheses) as data are accumulated.

Avoiding Spurious Results

This chapter has been a basic outline of the general philosophy and guidance of the analytical approaches the network will use, and as a final component it is essential to identify the possible pitfalls associated with analyzing natural resource monitoring data. These concerns are mostly based on the overemphasis of statistical analysis as a replacement for well-designed, objective-based design and analysis and were recently reviewed by Anderson et al. (2001).

To begin, data mining is a particular area that warrants caution. The problem with data mining is not its use as a tool for exploring data for possible relationships that warrant further investigation; rather, data mining is often inappropriately used as a hypothesis-testing tool instead of a hypothesis-generating tool. An example of possible data mining within the I&M program is co-location of samples under a generalized design. Although co-locating samples may generate new hypotheses, assuming that such insights will emerge without a priori thought about the expected relationships has a high risk of producing spurious results.

Another commonly encountered pitfall is the overuse or inappropriate use of statistical tests of significance (Cherry 1998). One problem is overuse of null hypothesis testing, which may have little or no biological meaning (Anderson et al. 2000). Another problem is that statistical tests are usually based on probability (e.g., Yates 1951, Cox 1977, Cherry 1998, Anderson et al. 2000) with an arbitrary P=0.05 level frequently used as a standard. Such an arbitrary threshold may have little or no relationship with what is considered biologically meaningful (Cherry 1998).

A corollary concern relates to analysis of multidimensional data. Multidimensional data often have an inherently complex structure that, when analyzed using many common multivariate statistical techniques, have a high probability of producing spurious results (Rextad et al. 1988, Anderson et al. 2001). This is less a result of inherent flaws with the underlying statistical theory of such approaches as it is a tendency for the practitioners to extend the inference beyond the analysis. James and McCulloch (1990) reviewed this topic and concluded that such approaches "can only hint at roles, processes, causes, influences and strategies". Other authors (e.g., Stauffer et al. 1985, Flack and Chang 1987) have recognized that "statistically significant" results can emerge even when the source data are random numbers. Therefore, while multivariate methods may be a valuable exploratory tool, interpreting these approaches as emerging ecological insights should be approached with caution.

GRYN Analysis Summary

In the previous sections of this chapter, we described the general philosophy and types of analyses we anticipate for the GRYN program. Here we summarize specific analyses we anticipate for those vital signs for which the development has reached this stage.

1. AMPHIBIANS

Estimating Occupancy Our measure of amphibian populations, and changes in those populations, would be based on the proportion of sites occupied (MacKenzie et al. 2002). This measure: (1) explicitly enables estimation of local extinctions and colonization rates (MacKenzie et al. 2002); (2) takes into account detectability of individual species (MacKenzie and Kendall 2002); (3) enables estimation of confidence intervals; (4) is comparable across sites and

(5) is becoming a widely accepted approach for reliable estimates of occupancy.

The general canonical estimator of occupancy follows that of capture-recapture models where the estimate of the population is:

$$\text{Population} = \frac{\text{Count}}{p}$$

where the count represents the number of animals observed and p represents the proportion of the animals present that are detected (Nichols 1992). Occupancy is an extension of this estimator such that:

$$\text{Occupancy} = \frac{\text{Presence}}{\hat{p}}$$

where occupancy of a given site can be represented over time and/or space as an encounter history where the sample occasion is assigned a "1" if the species is observed to be present and a "0" otherwise. In this fashion, an encounter history can be constructed such that 101 represents a species that was observed on the first sampling occasion, not observed on second sampling occasion, and observed again on the third (last) sampling occasion. From this encounter history likelihood can be constructed such that the likelihood for occupancy of site i with encounter history 01010 is:

$$\Psi_i = (1 - p_{i1})\, p_{i2}\, (1 - p_{i3})\, p_{i4}\, (1 - p_{i5})$$

and for which covariates can be incorporated into the model as a logistic model. Model selection (e.g., using AIC or alternative approaches) can then be incorporated to evaluate a suite of models with and without spatial or temporal effects including covariates of interest. Two software programs, PRESENCE (Mackenzie et al. 2003) and MARK (White and Burnham 1999) were developed for estimating a variety of parameters using marked individuals and can accommodate occupancy estimation and associated parameters. Both programs are available free of charge.

2. LANDBIRDS

Our field sampling approach for monitoring landbird populations is based on distance sampling (Buckland et al. 1993, 2001) with some minor refinements in the design to facilitate estimation of some parameters. Our objectives, and consequently analyses would focus on estimating the (1) distribution of select species within a given habitat of concern, (2) the abundance (density) of select species within a given habitat of concern, and (3) the community composition (e.g., species richness) within a given habitat of concern. The specific species of concern would be those that are obligates or depend substantially on the habitat of concern and species that have particular management interest or relevance.

Estimating Distribution The estimation of site occupancy, as described for amphibians, would be our primary type of analysis for evaluating distribution and changes in distribution. However, as it was originally conceived (e.g., MacKenzie et al. 2002) multiple visits to a given site over time is used to estimate detectability. In this framework the presence-absence (encounter history) of a given species is defined as a binary random variable assigned as 1 if a given species is detected at site i at time t and 0 if a given species is not detected at site i at time t. A problem for application of this framework for monitoring landbirds within the GRYN is that a given site will not be visited more than once within a year. Thus, an alternative is to consider replication over space rather than time. For this approach, the transect is considered as the sampling unit and the presence-absence of a given species is similarly defined as 1 if a given species is detected at a given point or section along the transect and 0 if otherwise.

Based on our sampling design we have drawn a sample of units (transects) from a given habitat type. Thus, the general inference for a given species that can be derived from this approach is to estimate the proportion of a given habitat type that is occupied by that species.

The general likelihood for estimating site occupancy was described by MacKenzie et al. (2002), and estimation of occupancy and its variance can be accomplished using either program PRESENCE (Mackenzie et al. 2003) developed explicitly for estimating occupancy and associated parameters, or the more general program MARK (White and Burnham 1999) developed for estimating a variety of parameters using marked individuals. Both programs are freely available and can be downloaded.

Estimating Abundance (Density) The estimation of density based on distance sampling would be the primary analysis for our objective related to abundance. Distance sampling represents a unification of its precursors in transect sampling (Hayne 1949, Eberhardt 1968, Gates et al. 1968, Burnham and Anderson 1976, Burnham et al. 1979) and variable circular plot sampling (e.g., Ramsey and Scott 1979) and has been summarized in considerable detail by Buckland et al. (1993, 2001). Central to the concept of distance sampling is the detection function. This is the probability of detecting an object, given that it is at a specified distance from the transect line or point. Using this approach, our primary analyses would be deriving estimates of species specific densities within our habitats of interest. Details of how detection functions are constructed and selected is beyond the scope of this report and provided by Buckland et al. (2001). Available software (Program DISTANCE) (Thomas et al. 2004) is available free of charge and accommodates a full suite of options for estimating parameters, incorporating covariates and selecting among alternative models using the model selection concepts described earlier in this chapter.

Estimating Community Level Parameters Biological diversity is recognized as one of the core indicators of the productivity and sustainability of the earth's ecosystems (Christensen et al. 1996, Nichols et al. 1998). Additionally, the protection of native species and their habitats is one of the primary challenges outlined in the NPS Natural Resource Challenge (National Park Service 1999). Thus, estimating species richness and change in species richness over time will be integral components of our analyses of bird monitoring data. One of the problems with estimating species richness from observations of animals is that, like individuals within a population, all species are not detected with equal probability (Boulinier et al 1998). To account for this concern an approach was developed that incorporates detection probabilities derived from encounter histories using the general approached described above for estimating occupancy (Boulinier et al. 1998, Nichols et al. 1998). Software to estimate species richness and associate parameters using this approach (i.e., program COMDYN) (Hines et al. 1999) is also available free of charge.

For the GRYN, one of the primary parameters of interest is not just species richness, but relative species richness. Nichols et al. (1998) defined relative species richness as the ratio of species richness for two locations, which is estimated as:

$$\hat{\lambda}_i^{xy} = \frac{\hat{N}_i^y}{\hat{N}_i^x}$$

Relative species richness, as defined by Nichols et al. (1998) enables comparison among areas receiving different management or experiencing different disturbances. An additional application would be to include relative species richness among groups of interest. For example, we may be interested in the ratio of native species to exotics. We would anticipate also assessing how the ratio of such groups (e.g., native and exotics) is changing over time.

3. Whitebark Pine

Estimating the Proportion of Infected Trees One of the key parameters we want to estimate for whitebark pine monitoring is the proportion of trees infected. There are two widely used approaches for such estimates from two-stage cluster designs, an unbiased estimator and a ratio estimator. An unbiased estimator certainly sounds intuitively appealing, since knowingly allowing bias seems undesirable. However, this estimator tends to be inefficient when cluster sizes (i.e., the primary sampling units) are of unequal size (as is the case for whitebark pine stands) and when the population sizes of the primary sampling units tends to be proportional to the cluster sizes (as we might also expect for whitebark pine). Further, the variance derived from this estimator tends to be large when cluster sizes are unequal. The alternative approach, to which we are most likely to use, is a ratio estimator. The variance of the ratio estimator has two components; one measuring the between cluster variability and one measuring the within cluster component. Although the ratio estimator is biased, it is preferred in this case because the bias tends to be very (negligibly) small and the precision of our estimates would likely be substantially better than for the unbiased estimator. The formula of these estimators, including the variance components can be somewhat complicated and are readily found in most sampling texts (e.g., Lohr 1999). We would use the same analysis approach to estimate the mean severity index.

Estimating Survival There are several analytical approaches (models) available for data in which the status (i.e., fate in the context of survival estimation) of an individual can be determined at any given time. Whitebark pine would fit into this category because all trees in our sample have been individually marked and trees do not move between sampling occasions (at least with respect to determining their fate). These known-status models can be further classified based on how they treat time (Conroy et al. 1996). In one approach, time corresponds to the discrete intervals separating sampling periods and survival is viewed as a binomial process. Thus, familiar statistical models (e.g., logistic regression) can be applied (Nichols 1996). The second class of models is based on time to a specified event (e.g., death or censoring) (Lee 1980). We anticipate using both approaches in our analyses of whitebark pine. Time-to-event models such as the Kaplan-Meier estimator (Kaplan and Meier 1958) would likely be used for deriving estimates of survival and its variance; whereas, discrete interval models, such as logistic regression, would likely be used in the context of evaluating the effects of covariates on survival.

4. CLIMATE

Climate is a primary driver of almost all physical and ecological processes in the GRYN. As such, most of our analyses are likely to be descriptive summaries at various spatial and/or temporal scales that would be used in a variety of contexts including assessment of change and as covariates for analyses of other vital signs.

Primary Climatic Elements For our primary climatic elements (i.e., temperature and precipitation), we would anticipate the flowing summaries at a minimum:

Daily Summaries

- Daily Precipitation (mm)
- Daily minimum and maximum temperature (° C)

Monthly Summaries

- Mean monthly precipitation intensity (mm)
- Mean monthly minimum and maximum temperature (° C)
- Number of wet and dry days
- Number of days with temperature below 0° C
- Number of days with temperature above 35° C

Annual Summaries

- Mean annual precipitation intensity (mm)
- Mean annual minimum and maximum temperature (° C)
- Number of wet and dry days
- Number of days with temperatures below 0° C
- Number of days with temperatures above 35° C

Secondary Climatic Elements For our secondary climatic elements, we would anticipate the flowing summaries:

15-minute intervals

- Wind Speed (m/s)
- Wind Direction (degrees)
- Relative Humidity (percentage)
- Soil Surface/Near Surface Temperatures (~10 cm) (° C)

Hourly

- Incoming Solar Radiation (W/m2)

Daily

- Soil Temperatures at Depth (~ 1 m)
- Daily mean, minimum and maximum (° C)

5. LAND USE

Changes in characteristics of land use and cover are usually expressed as rates of change from one time period to the next. Change in all of the metrics described above for land use will be assessed in this way. Specifically, percent change will be calculated as [(current value – value at last time period)/value at last time period]. For example, if there are 50 rural homes in a given section in one time period, and 75 homes in the next time period, the rate of change would be [(75-50)/50] = 0.5, or 50%. Rates of change in characteristics of land use can be charted starting with the second monitoring time period and trend analysis should occur at each monitoring time period after that. Additionally, trajectories of change can be calculated by overlaying maps from two time periods.

6. WATER QUALITY

Once the water quality data have been collected, they will be summarized and presented in an organized manner. This will help identify potential outliers or errors. Descriptive statistics (readily available with the MS Excel Data Analysis Toolpak) should be performed for all data collected. Data will be summarized in this manner each time results are received (from lab or field). These statistics include:

- Mean
- Standard Error
- Median
- Mode
- Standard Deviation
- Sample Variance
- Kurtosis
- Skewness
- Range
- Minimum
- Maximum
- Sum
- Count
- Confidence Level (99.0%)

Routine trend and other standard statistical analyses will be done according to Helsel and Hirsch (1992), which has been re-published as an online text at: http://water.usgs.gov/pubs/twri/twri4a3/html/pdf_new.html.

REPORTING

For the GRYN to be successful in communicating its purpose and progress toward inventory and monitoring, it is essential for the network to focus on the following internal audiences: 1) the National I&M Program and Congress; 2) the GRYN Board of Directors, Technical Committee and Science Committee; 3) Yellowstone National Park, Grand Teton National Park and Bighorn Canyon National Recreation Area park managers and employees; and external audiences, including: 4) the academic community; 5) other government agencies; 6) nonprofit/non-governmental organizations; and 7) the general public. Reports directed towards these audiences, including the purpose and frequency of each report, are described in Table 7.1. This list includes both those reports required by the National I&M Program and additional reporting mechanisms developed by the GRYN to communicate its progress in an effective manner. These reports should also provide a source of accountability for mandates, such as the Government Performance and Results Act, as outlined in the Strategic Plan.

In addition to developing reports for the aforementioned audiences, the GRYN will begin the task of expanding its reporting procedures through a Web-based interface. This Web-based communication mechanism will allow the GRYN to provide background data and information to a large audience with relative ease, compared with printed reports. The network is also pursuing a Web-based interface due to its easy accessibility by park managers and the ease with which it may be updated when new information is acquired. A possible format for the design of the Web-based interface is included in Figure 7.4.

Making the Reporting Relevant

The greatest science in the world will do us little good if it does not find its way into the management decision process. The goal of the GRYN is to provide the right type of information, in the right form, to the right people, at the right time. Previous discussions in this report regarding selection of vital signs and determining the objectives focused on obtaining the right type of information. Getting it in the right form, to the right people, at the right time is a different matter altogether.

It is naive to assume that the form in which information is distributed to the scientific community (e.g., technical reports and peer-reviewed journal articles) will be equally useful to managers. Scientific articles and reports serve to establish the credibility of the information, but do little to ensure the utility of the information. Effective transfer of information will not likely occur without consideration of the audience and the needs of that audience. For example, the scientific community would likely need to see detailed methods, statistical analyses, models, etc. to establish the validity of the science. In contrast, such detailed information might be excessively cumbersome for a park superintendent who may need a synthesis of the information (see text box 7.1 on the following page) that is concise, understandable and applicable to the management context.

Getting the information in the right form also requires recognition that, in addition to the network distributing information in various forms to different users, users also seek information from the network, most notably via the Internet. This group of users can be loosely divided into casual or opportunistic users, who obtain information from the network infrequently and for specific purposes or just through Web surfing. For network information to be useful to this group, the information must be accurate, interesting and well presented. Another anticipated subset of users within those that seek information from the network is those that use the network information as a routine resource. For this group, the information must meet all of the standards above but must also be consistent in presentation and form. Users intending to use the network as a resource may quickly lose interest if they find it difficult to find the information they need and/or the information is not of consistent form and quality. Consequently, our Web-based information delivery will incorporate a hierarchical structure that should enable different targeted audiences to quickly find the information that they need and in a usable form (Figure 7.5).

FIGURE 7.4 Example of hypothetical Web site that might be used to report information being distributed by the GRYN.

TEXT BOX 7.1 Example of Synthesis Intended for Park Managers

Each year, in an effort to increase the availability and usefulness of monitoring results for park managers, the network coordinator will take the lead in organizing a one-day "Science briefing for park managers" (possibly in conjunction with other resource management workshops currently being conducted by network parks) in which network staff, park scientists, USGS scientists, collaborators from academia, and others involved in monitoring the parks' natural resources will provide managers with a briefing on the highlights and potential management action items for each particular protocol or discipline. These briefings may include specialists from the air quality program, fire ecology program, Research Learning Center, and collaborators from other programs and agencies to provide managers with an overview of the status and trends in natural resources for their parks. Unlike the typical science presentation that is intended for the scientific community, someone representing each protocol, program, or project will be asked to identify key findings or "highlights" from the past year's work and to identify potential management action items. The scientists will be encouraged to prepare a one or two page "briefing statement" that summarizes the key findings and recommendations for their protocol or project; these written briefing statements will then be compiled into a 'Status and Trends Report' for the network. In the process of briefing the managers, the various scientists involved with the monitoring program will learn about other protocols and projects, and the process will facilitate better coordination and communication and will promote integration and synthesis across disciplines.

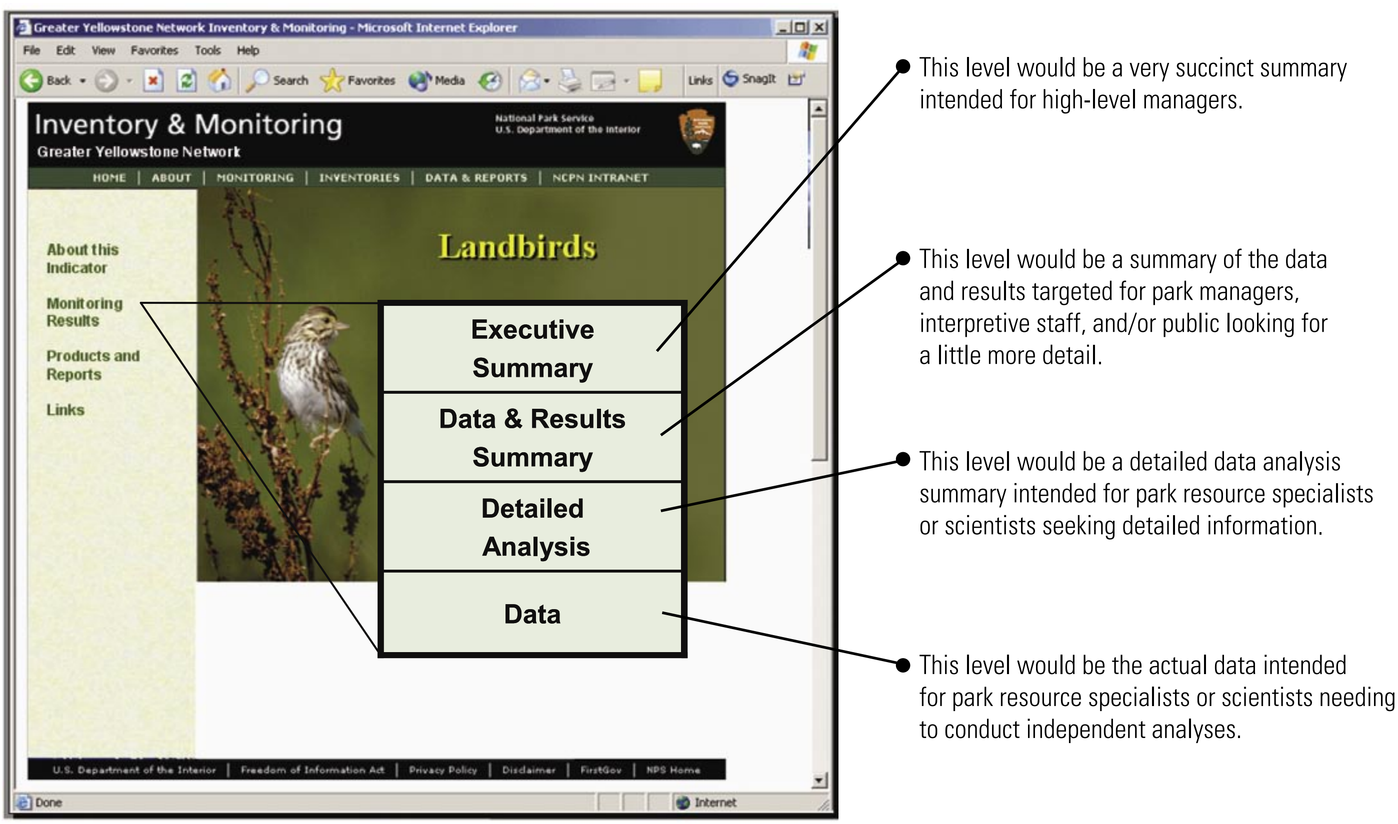

FIGURE 7.5 Example of hierarchical structure of results that would target different audiences.

The timing of our reporting is also critical for making information useful. Providing a manager with important new information about the effects of fire on an ecosystem three months after the fire management plan is due is not an effective way to incorporate learning into decisions. In contrast, knowing something about when decisions are made can be a great asset if information delivery is planned from the outset to coincide with when decisions are made. Clearly, communication between scientists and managers will shed some light on this issue, but another form of conceptual model can also help to clarify this information. One approach that the GRYN will use to help facilitate timely delivery of information will be to develop a simple model of the decision space (Figure 7.6). Such a model can include processes or plans for which decisions are expected. It can also include relevant information about who the key players are for a given decision. Unfortunately, it will not likely include all of the decisions for which information would be useful and, thus, will not replace the need for communication.

Even with the right type, form and timing of information, there still needs to be a planned mechanism to effectively enable monitoring information to influence the decision process. There have been a wide variety of approaches for integrating information into the decision process, ranging from formal mathematical procedures for deriving an optimal policy using discrete stochastic dynamic optimization (e.g., Kendall 2001) to scientists and managers simply sitting down at the table to discuss the implications of the science to management. The GRYN does not advocate that the decision process must follow a specific approach; instead, we advocate using the most suitable approach for a given context and suggest that the approach should be explicit and planned.

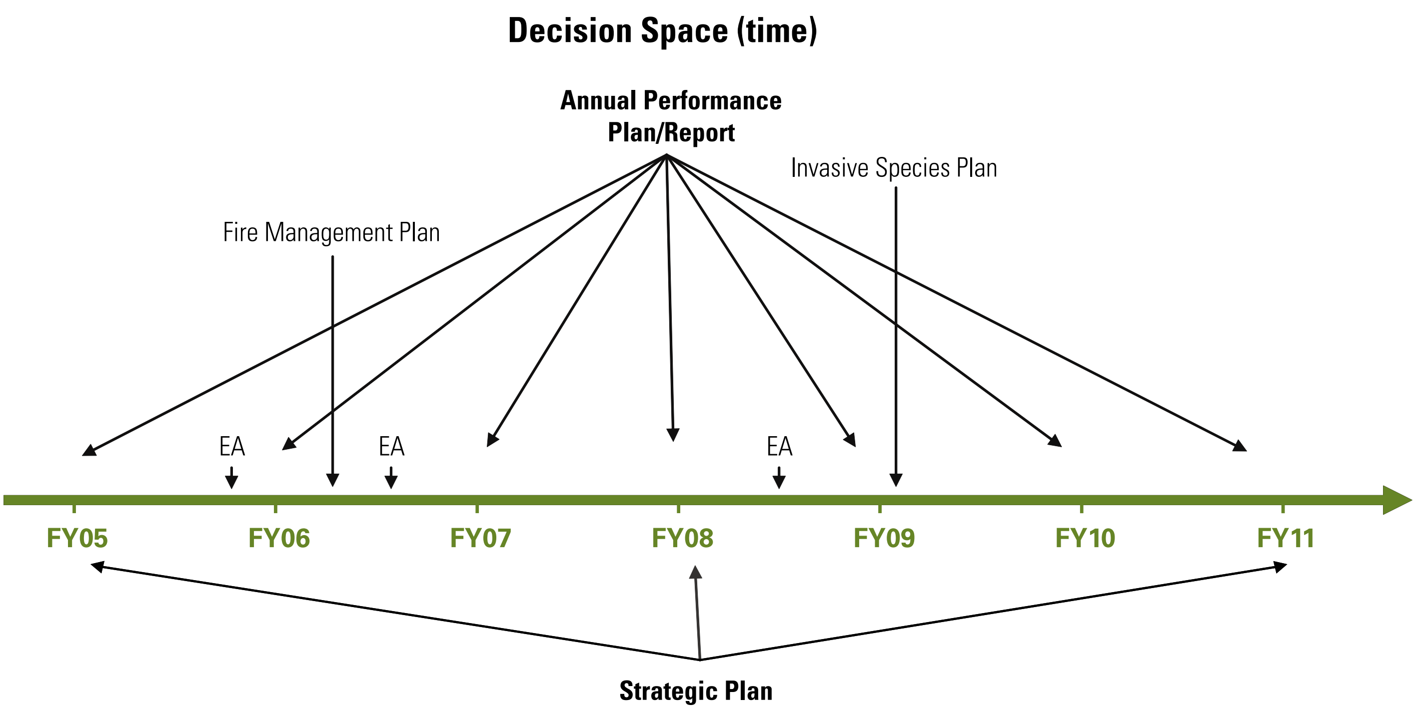

FIGURE 7.6 A conceptual model of the decision timing (e.g., plans likely to require decisions) for a given national park.

TABLE 7.1 Reports developed by the GRYN, including the frequency, purpose, author and format of each report.

Title	Purpose of Report	Frequency	Primary Audience	Author	Format
Annual Administrative Report and Work Plan	Account for funds and FTEs expended. Describe objectives, tasks, accomplishments, products and budget for the previous year and those proposed for the following year	Annual; due to WASO with draft work plan in early November and final work plan by January 31	Superintendents, technical committee, GRYN staff, regional coordinators and service-wide program managers. Administrative report used for annual report to Congress	Network program manager, with additional input from network staff; Technical Committee reviews; Board of Directors approves	Format of the report is outlined by the service-wide I&M program each year
Monitoring Protocols	Document the rational for why a particular resource is being monitoring and describe measurable objectives, sampling design, field methodology, data analysis and reporting, personnel and operational requirements	Once for each vital sign (or group of vital signs), with revisions as needed	Network staff and others who implement all or portions of the monitoring protocol	Individual investigators or responsible GRYN staff	Should follow the guidance outlined in Oakley et al. 2003 (see also Chapter 5)
Inventory Project Reports	Document the methods and results of the inventory project; provide a list of species officially documented and locations sampled	At least once at the end of the inventory, although annual progress reports are recommended	Superintendents, park resource managers, GRYN staff, service-wide inventory program managers, external scientists and public	Inventory project leader	Varies by project
Trend Analysis and Synthesis Reports	Describe and interpret trends of individual monitored resources in order to provide a picture of overall ecosystem health. Highlight resources in need of management action	Trend Analysis and Synthesis Reports at 5 year intervals	Park resource managers, GRYN staff, external scientists and interested public	Network staff (particularly the ecologist)	To be determined
Program Review Reports	Review operations and protocols and determine needed changes. Used as a formal review of program and protocols	Five-year intervals, starting in 2008	Superintendents, technical committee and GRYN staff	Initiated by program manager, with input from staff and cooperators	To be determined
Annual Report to Superintendents	Summarize annual activities of the network. Highlight key findings and recommendations for non-technical audiences	Annual	Superintendents, park staff and interested public	Program manager, with staff contributions	To be determined

Journal Articles and Book Chapters	Document and communicate advances in knowledge	Variable	External scientists, park resource managers	Program manager, staff and cooperators	Determined by journal or book publisher
Symposia, workshops and conferences presentations	Communicate I&M goals, network activities and specific results. Review and summarize latest findings and emerging issues	Variable	Symposia, workshop and conference participants	GRYN staff	Varies
GRYN newsletter	Describes current happenings in the GRYN and findings of general interest.	Quarterly	Park staff, agency partners and cooperators	GRYN staff	Follows standard newsletter format
Public Brochures	Describe ongoing monitoring efforts and problem statements pertaining to vital signs of interest	Variable	To provide a synopsis of the reasons for monitoring various vital signs in a format written for the general public	GRYN staff (generally, ecologist and research associate)	Varies; should generally follow the format for whitebark pine for interagency projects
Data Management Report	Describes the plan for managing data pertinent to GRYN monitoring	Final version complete in FY05, with continual revisions as needed	GRYN and park staff	Data manager (with help from other network data managers)	Determined by national data management report team of authors
Web site	Online method for distributing information about GRYN activities	To be determined	Various audiences; Web design offers multiple levels of information	Data manager (with help from a Web designer)	To be determined